# AN ENHANCED METHOD FOR DETECTING MICROANEURYSMS

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**Abstract:** Diabetic retinopathy (DR) is one of the complications of diabetes that develops in most of the patients with long- standing illness, and the leading cause of blindness in the developed countries. Effective treatments for DR are available, though it requires early diagnosis and the continuous monitoring of diabetic patients. Diagnosis of DR is performed by the evaluation of retinal (fundus) images. Manual grading of these images to determine the severity of DR is rather slow and resource demanding. The presence of micro aneurysms (MAs) on the retina is the first and most characteristic symptom of this disease. MAs on the retina appear as small, round shaped, red dots. In existing we did not apply any additional vessel or optic disk detection step. The proposed method proved to be able to distinguish vessel bifurcations and crossings from MAs rather well; however, some of the false positives come from the region of the optic disc. MAs-like structures do appear on the optic disc, and since the contrast is very high in this region, sometimes a rather high score is assigned. The presences of abnormalities in the retina such as the structure of blood vessels, micro aneurysms, and exudates using image processing techniques are detected.

**Index Terms:** Biomedical image processing, cross- sectional scanning, feature calculation, image classification, medical decision-making, pattern recognition, peak detection.

## 1. INTRODUCTION

Diabetic Retinopathy(DR) is mainly caused by the changes in the blood vessels of the retina due to increased blood glucose level. Exudates are one of the primary sign of Diabetic Retinopathy. Exudates are yellow-white lesions with relatively distinct margins. Exudates are lipids and proteins that deposits and leaks from the damaged blood vessels within the retina. Detection of Exudates by ophthalmologists is a laborious process as they have to spend a great deal of time in manual analysis and diagnosis. Moreover, manual detection requires using chemical dilation material which takes time and has negative side effects on patients. Hence automatic screening techniques for exudates are preferred. In order to develop a solution for automatic DME assessment, first a decision module is required to validate the presence or absence of HE in a given color fundus image. Once their presence is confirmed, a second 1module has to assess the macular region for measuring the risk of exhibiting DME.

Diabetes can also cause other retinal complications all of which are collectively termed as diabetic retinopathy (DR). Given the potential for vision loss and blindness due to DR, screening programs have been launched in many countries and color fundus image forms the basis for manual assessment in screening. Such manual assessment however is not scalable in large-scale screening scenario, particularly in developing countries either due to the scarcity of skilled manpower or unavailability of high end imaging equipment at the point of care. Solutions such as screening using permanent and mobile units to enable screening of retinal disorders in remote areas have been proposed. In such a scenario, an automatic disease detection system can significantly reduce the load of experts by limiting the referrals to those cases that require immediate attention. The reduction in time and effort will be significant where a majority of patients screened for diseases turn out to be normal. The ratio of normal patients to the ones showing disease symptoms can be as high as 9 to 1 in DR screening. Several attempts have been reported towards building an automated solution for DR detection. Motivated by these attempts, we aim to develop a solution for automatic assessment of DME from color fundus images. Such a solution will be a value addition to the existing infrastructure of DR screening.

DME detection, the strength of local schemes is the ability to detect small HE while the global schemes remove the burden of having to

detect/segment every HE. It aim to explore using the global characteristics of an image while retaining the sensitivity to small HE. Towards this, we propose to transform the given image to an intermediate representation called motion pattern that spatially enhances the HE presence regardless of their size. This is followed by derivation of global features on the motion pattern for detection of HE.

## 2. RETINAL BLOOD VESSEL SEGMENTATION

In the framework of computer-aided diagnosis of eye diseases, retinal vessel segmentation based on line operators is proposed. A line detector, previously used in mammography, is applied to the green channel of the retinal image. It is based on the evaluation of the average grey level along lines of fixed length passing through the target pixel at different orientations. Two segmentation methods are considered. The first uses the basic line detector whose response is threshold to obtain unsupervised pixel classification. As a further development, we employ two orthogonal line detectors along with the grey level of the target pixel to construct a feature vector for supervised classification using a support vector machine. The effectiveness of both methods is demonstrated through receiver operating characteristic analysis on two publicly available databases of color fundus images. Digital fundus imaging in ophthalmology plays an important role in medical diagnosis of several pathologies like hypertension, diabetes, and cardiovascular disease. Computer-aided image analysis of the eye fundus is highly desirable in many cases. For example, the diagnosis of diabetic retinopathy, the leading cause of blindness in the Western World, requires the screening of a large number of patients from specialized personnel and can be extremely facilitated with the adoption of automatic tools.

In this research, we explore a computationally simpler but more effective realization of the same concept, inspired by a research of Zwiggelaar about the detection of linear structures in mammographic images. Among the techniques compared, select the line operator introduced which has been modified to take into account the peculiarities of retinal vessel structure. The resulting image is threshold to obtain unsupervised binary pixel classification. Then, to further improve the performance, a supervised method is proposed where two line detectors are used to compute the feature vectors, while a linear support vector machine (SVM) is chosen as a classifier. With respect to previous supervised techniques, the proposed method exhibits the following desirable properties: it requires less features, feature extraction is computationally simpler, and fewer examples are needed for training. The performance of both methods is evaluated on the publicly available STARE and DRIVE databases through receiver operating characteristic (ROC) analysis. From the area under the ROC curve and from the accuracy.

## 3. AUTOMATED MICRO ANEURYSMS DETECTION

Screening programs for diabetic retinopathy are being set up in the U.K. with the aim of detecting and treating the disease before it causes blindness [2]. These are based on digital photography of the retina with or without my driasis (pupil dilation). Automated analysis of retinal images has the potential to reduce the screening program costs compared to manual image grading. Diabetic retinopathy produces a variety of lesions on the retina. Of these, micro aneurysms (MAs) are likely to be the only lesion present at the earliest stage of the disease and continue to be present as the disease develops. Thus MAs are of major importance for automated retinopathy detection. Since retinopathy is present in only 30% of the diabetic population, automated detection of MAs has the potential for a large reduction of the manual grading workload. Hip well that an automated MA detection system can reduce the workload by 50%. According to the severity of retinopathy, manual graders would decide whether a patient should be recalled at the normal or reduced screening interval or whether referral to an ophthalmologist is required. MAs are swellings of the capillaries caused by a weakening of the vessel wall. In retinal photographs, although the capillaries are not visible, MAs appear as dark red isolated dots. In common with vessels, MAs appear with highest contrast in the green plane of the color image.

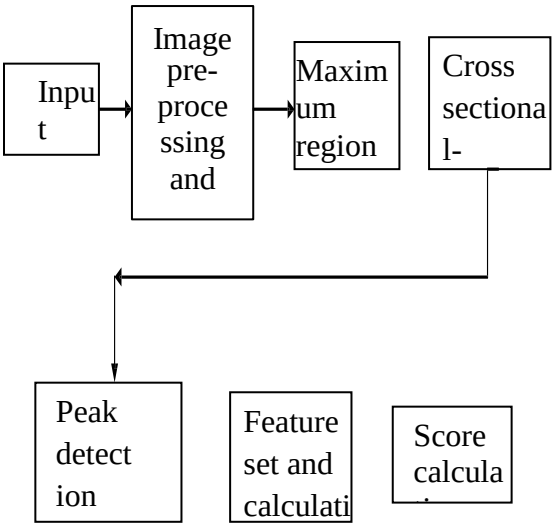
Contrast normalization is most safely performed with a method which reliably avoids including vessels in the contrast estimate. Localized vessel detection improves MA detection. More cost effective. Not identifying other feature in retinal image.

## 4. A SUCCESSIVE CLUSTER-REJECTION

Diabetic Retinopathy (DR) is a major public health issue since it can lead to blindness in patients with diabetes. Micro aneurysms (MAs) are usually the first clinical symptom of DR[3]. They are swellings of capillaries caused by a weakening of the vessel wall. Their sizes range from 10μm to 125μm. In the clinical scenario, experts rely either on direct manual examination or fluorescein fundus angiography where MAs appear with high contrast as bright white spots. Given the high cost and the cumbersome requirement of intravenous injection of a dye for this type of imaging, interest in the recent past has been on detecting MAs from a color fundus/retinal image(CFI). In CFIs, MAs appear as tiny, reddish isolated dots. Automatic detection of MAs from digital CFIs can play an important role in DR screening at a large scale. It can significantly reduce the workload of the ophthalmologists and the health costs in the DR screening.

The presence of micro aneurysms (MAs) is usually an early sign of diabetic retinopathy (DR) and their automatic detection from color retinal images is of clinical interest. In this research, we present a new approach for automatic MA detection from digital color fundus images. MA detection as a problem of target detection from clutter, where the probability of occurrence of target is considerably smaller compared to the clutter has been formulated. A successive rejection-based strategy is proposed to progressively lower the number of clutter responses. The processing stages are designed to reject specific classes of clutter while passing majority of true MAs, using a set of specialized features. The true positives that remain after the final rejecter are assigned a score which is based on its similarity to a true MA. Results of extensive evaluation of the proposed approach on three different retinal image datasets is reported, and are used to highlight the promise in the presented strategy.

Retinal images are widely used by ophthalmologists and primary care physicians for the screening of epidemic eye diseases, such as Diabetic Retinopathy (DR). DR is one of the leading causes of blindness and vision defects in developed countries. Due to its prevalence and clinical significance the research community has attempted to improve its diagnosis and treatment by developing algorithms to perform retinal image analysis. Retinal images permit a high quality permanent record of eye fundus for detecting early signs of DR and monitoring its progression.




## 5. METHODOLOGY

### 5.1 Image Preprocessing

The proposed method particularly relies on the local intensity distribution of MAs, it is important to reduce the effect of noise. In this convolution with a Gaussian mask with a variance of 1.0. This amount of smoothing suppressed noise sufficiently while preserving true Mas.

### 5.2 Local Maximum Region Extraction

A simple breadth-first search algorithm applied for the calculation of gray scale morphological reconstruction. Pixels of the image are processed sequentially, and compared to their 8-neighbors. If all 3eighbours have a lower intensity, then the pixel itself is a LMR. If there is a neighboring pixel with higher intensity, then the current pixel may not be a maximum. Pixels of a LMR are considered individually as possible candidates and the pixel with the maximum final score will represent the region; this procedure is referred to as non-maximum suppression.

MAs are local intensity maximum structures on the preprocessed retinal image, usually with a Gaussian like intensity distribution. This means that every MA region contains at least one regional maximum also. A local maximum region (LMR), of a gray scale (intensity) image is a connected component of pixels with a given constant intensity value, such that every neighboring pixel of the region has a

strictly lower intensity [27]. Therefore, it is sufficient to consider only the LMRs of the preprocessed image as possible MA candidate regions. In our implementation, we applied a simple breadth-first search algorithm, similar to the one described in [27] for the calculation of gray scale morphological reconstruction. Pixels of the image are processed sequentially, and compared to their 8-neighbors. If all neighbors have a lower intensity, then the pixel itself is a LMR.

If there is a neighboring pixel with higher intensity, then the current pixel may not be a maximum. A pixel is considered to be a possible maximum if all neighboring pixels have lower or the same intensity, in which case pixels with the same intensity are stored in a queue, and tested in the same way. If eventually the queue is emptied so that all the pixels it contained proved to be possible maxima, then the corresponding connected component is a LMR. Pixels of a LMR are considered individually as possible candidates, and the pixel with the maximum final score will represent the region; this procedure is referred to as non-maximum suppression, and it will be discussed in details later on. We note that the usage of image smoothing, as discussed in the previous section, gains importance at this point, since the local intensity variations may be high on a raw retinal image, resulting in many local maxima.

### 5.3 CROSS-SECTIONAL SCANNING

To examine the surrounding of a single maximum pixel in a MA candidate region, the intensity values along discrete line segments of different orientations, whose central pixel is the candidate pixel, are recorded. In this way, we obtain a set of cross-sectional intensity profiles.

### 5.4 Peak Detection and Property Measurement

On the obtained cross-section profiles a peak detection Step is performed. Our aim is to decide whether a peak is present at the center of the profile, i.e., at the location of the candidate point for a specific direction. We calculate several properties of the peak, and the final feature set consists of a set of statistical measures that show how these values vary as the orientation of the cross-section is changing. This way, the variation of important characteristics, such as symmetry and shape of the structure and its difference from the background may be numerically expressed.

The basis of the peak detection method we apply is to locate strictly monotonic segments (ramps) of the profile. Let P denote a profile and P[i] its ith value. A ramp is defined as a segment of the profile, i.e., P[m],P[m+1],…P[n] where the sign of the difference between the consecutive values is non- zero and the same along the segment, i.e., sgn(P[i]-P[i-1])=sgn(P[i+1]-P[i])for every m<i<n. Additionally, the absolute difference between consecutive values should not be less than parameter min diff, and the height of the ramp, i.e., the absolute difference between the first and last value should be not less than parameter min height, either. The value of min defects as a lower threshold for the slope of the ramps, and it control show sharp the intensity transition should be. The purpose of the min height parameter is to give a lower noise threshold. Based on whether sgn(P[i+1]-P[i]) is positive or negative the ramps are considered to be increasing or decreasing ramps, respectively. We have examined the cross- section profiles of several Mas, and found that by setting min diff to 2, and the min height to 3, small monotonic segments that are clearly noise artifacts can be eliminated.

The value of peak width corresponds to the extension of the structure in the considered direction. The top width measures how large the maximum area in the structure is. The heights and slopes of the increasing and decreasing ramps provide information about the distinction from the surroundings, and the sharpness of the intensity transition. We note that the slope is considered to be positive for decreasing ramps, too. The peak height value combines the heights of the increasing and decreasing ramps by fitting a baseline to the peak, and calculating the central pixels distance from it. The calculated peak measures except the slopes—on the previous sample cross-section profile.

### 5.5 Feature Set and Classification

After the cross-sectional scanning and peak detection steps are performed for every scan direction on a given candidate we calculate several statistical measures of the resulting directional peak properties. The increasing-and decreasing ramp height values are stored in the RHEIGHTS set, likewise, the ramp slope values are stored in RSLOPES. The TWIDTHS, PWIDTHS, and PHEIGHTS sets contain the top width, peak width, and peak height values, respectively. Let

$\mu_t$ , $\sigma_t$ and $CV_t$ denote the respective mean, standard deviation and coefficient of variation of the values in set T, where the coefficient of variation is the ratio of the standard deviation and the mean, i.e., CV =σ/μ . We consider the following feature set for classification:

$$F = \{\mu PWIDTHS, \sigma PWIDTHS, \mu TWIDTHS. \sigma TWIDTHS, \sigma RSLOPES, cv\ RHRIGHTS, cvp\ HEIGHTS\}$$

For classification, we used a naïve Bayes (NB) classifier, a simple and robust probabilistic algorithm that assumes the individual features to be independent. The training set consists of both positive and negative MA examples. Usually, it is rather straightforward to obtain the feature vectors of positive instances of the training set, since in most public datasets the coordinates of Mas on the images are given. The non-MA set consists of the previously described most common false positives. The training of a NB classifier means the estimation of the class priors and feature probability distributions. We assume that the feature values in each class are of Gaussian distribution. This also means that the parameters of the distribution can be estimated using the sample means and variances of the training data for the given feature. We also consider the class priors to be equal. We have tested other classification methods, such as k-nearest neighbor (kNN), and support vector machines (SVMs) with different kernel functions, as well. Our experiments showed that there was only a minimal difference in the final performance, but NB gave a slightly better result. Besides, its low computational time and its robustness are also advantageous. However, it is not our intention to find the most suitable classification method, much rather to show the ability of the proposed feature set to express the important characteristics of MAs. The training set, different classifier results and the performance evaluation methodology will be discussed in details in the experimental results section.

### 5.6 Ma Score Calculation And Non- Maximum Suppression

To meet the requirements of a real-life DR screening system, score values are assigned to the MA candidates that were classified as true Mas, which score considers the shape, symmetry, sharpness and contrast of the candidate. The score is constructed in such a way that stronger, more visible Mas achieve higher score than faint ones.

The MA Score is calculated using the formula

$$Score = \frac{min_{PHEIGHTS} \cdot \mu_{RSLOPES}}{1 + \sigma_{PWIDTHS} + \sigma_{TWIDTHS} + \sigma_{RSLOPES} + \sigma_{RHEIGHTS} + \sigma_{PHEIGHTS}}$$

The final step of the proposed method is the non-maximum suppression. We have described earlier that in the case of regional maxima, all points of the region are considered as candidate pixels. Non maximum suppression at this point refers to the operation of selecting the point with the highest score from every maximum region that will represent the corresponding candidate. Therefore, points with non-maximal score in a candidate region are neglected, and the output of the proposed method is a set of coordinates and the corresponding score values. We note that the MA scores are not normalized values. Optionally, it is possible to have a binary output for the MA candidates with an appropriate thresholding of the score values.

The proposed method applies a two-class classification; therefore, it requires two sets of training examples. Assembling the positive (MA) set is rather straightforward. However, compilation of the negative (non-MA) set is more complicated, since its elements have to be selected manually. To construct the training feature set for the classifier of the proposed method, we took the official marking of the MAs on the training set as a basis, and we sorted out the ambiguous ones manually. The non-MA set consisted mostly of vessel crossings and bifurcations, elongated disconnected vessel fragments and haemorrhages.

## 6. CONCLUSION

In this paper, we have presented a method for the detection of MAs on retinal images based on the principle of analyzing directional cross-section profiles centered on the candidate pixels of the preprocessed image. The number of pixels to be processed is significantly reduced by only considering the local maxima of the pre-processed image. We apply peak detection on each profile, and calculate a set of values that describe the size, height, and shape of the central peak. The statistical measures of these values as the orientation of the cross-section changes constitute the feature set used in a

classification step to eliminate false candidates. We proposed a formula to calculate the final score of the remaining candidates based on the obtained feature values. Automatic Diabetic retinopathy eye diseases detection would be helpful for diabetic retinopathy screening Process. Early detection can potentially reduce the risk of blindness. In future an automatic method to detect Diabetic retinopathy eye diseases with improved performance is proposed.

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